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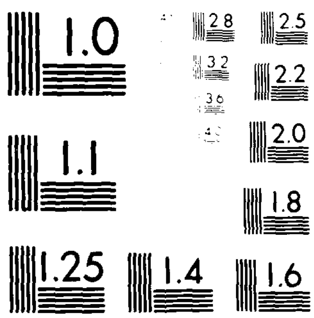

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A NOTE ON THREE-DIMENSIONAL TEXTURE

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ABSTRACT

Texture plays an important role in many image analysis tasks. In this note, we examine the role of three-dimensional texture analysis in three-dimensional image processing.

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Texture plays an important role in many image analysis tasks [1]. Visual textures may be regarded as complex patterns composed of subpatterns of characteristic brightness, color, slope, shape, etc. A texture then is a similarity grouping of subpatterns, and in general by texture, we mean the pattern of spatial distribution of grey level in an image. In this note, we examine the role of texture in three-dimensional (3D) image processing (i.e., 3D processing of 3D images).

The discussion here is focused on texture in images of three spatial dimensions, and not, for example, on multi-spectral or time-sequence imagery, which may be regarded as three-dimensional, with the third dimension representing wavelength or time. Images of three spatial dimensions are produced routinely by computed tomography. Since values in these images represent feature density in a volume of a scene, 3D texture is not associated with patterns of changes in brightness, luminance, hue, etc., on the surface of objects in the scene, but rather with patterns of feature density of the (solid) object. In time-sequence imagery, where texture derives from patterns on the surfaces of objects, the relation between 2D texture and 3D texture is completely determined by motion in the scene, camera, illumination source, etc. For multi-spectral images, it is more difficult to make this comparison, since the 2D monochromatic textures may have an arbitrary relationship with each other.

There have been four basic approaches to the measurement and characterization of two-dimensional texture (see [1] for a review): spatial frequency measurement, edgeness measurement, structural analysis, and co-occurrence probability measurement. Spatial frequency is related to texture in that finer textures have more high frequency content than coarse textures, and coarse textures have more low frequency content than fine textures. Similarly, coarse and fine textures may be differentiated on the basis of the amount of edge per unit area. In the structural approach a generalized autocorrelation is used as a matching procedure to detect regularity of elementary shapes in a binary image. Co-occurrence probabilities measure spatial distribution of grey level; coarse textures are those for which the distribution of co-occurrences of grey level changes slowly with distance, and fine textures are those for which the distribution changes rapidly with distance.

There is no doubt that each of these approaches extends straightforwardly to 3D image analysis. However, the larger amount of data in a 3D image and the additional degree(s) of freedom in the measurements render 3D texture analysis very costly computationally. The question then is not whether these texture analysis techniques will work in three-dimensions, but rather to what extent can 3D texture classifiers outperform 2D texture classifiers?

Inasmuch as these basic texture classification techniques are statistical in nature, we might expect that a 3D classifier

should outperform a comparable 2D classifier. That is, given a 2D technique measuring some feature of spatial frequency, edgeness, grey level co-occurrence, or similarity of elementary shapes in a given 2D neighborhood, we might expect that the additional data in a comparable 3D neighborhood would allow a reduction in the error of these measurements.

In the light of recent findings, such a viewpoint should be taken cautiously. For example, [2] compared 2D and 3D spatial averaging on synthetic images with normal noise. A 3×3 local average should reduce variance by roughly a factor of 3, and a $3\times 3\times 3$ local average roughly by a factor of $5.2=\sqrt{27}$. However, it was found that (presumably) because of the effect of blurring, the 2D operator may actually achieve a greater reduction in noise level (as measured by RMS error) than the 3D operator.

Secondly, since many of the 2D classifiers have been reported to achieve very high classification accuracy (some over 90%), it is difficult to imagine that this additional information of the 3D image could be used to obtain a significant improvement. Further, the most successful of these 2D classifiers rely on rather large neighborhood sizes (e.g., 16×16 as a minimum), so that the additional computational cost of a comparable 3D classifier (e.g., using a $16\times 16\times 16$ neighborhood) is substantial. Note that if, say, it is necessary to use an $N\times N$ 2D neighborhood in order to measure a sufficient number of texture elements with some statistical accuracy, it is unlikely that an $M\times M\times M$ 3D neighborhood, with $M^3\approx N^2$, will contain enough structural elements to achieve comparable accuracy.

On the other hand, it is not hard to display different 3D image textures which cannot possibly be distinguished by a 2D classifier operating on parallel cross-sections of the 3D image. For example, let the first texture consist of solid upright cylinders whose radii are distributed uniformly in the range [0,R], so that every horizontal cross-sectional image consists of circles with radii distributed uniformly in [0,R]. Let the second image consist of solid spheres of radius R such that the vertical coordinate of the center of the spheres has a uniform distribution. Further, let the distribution of spheres be such that the density distribution of cross-sections is equal to the density distribution of cross-sections of the cylinders in the first texture image (i.e., the distribution of areas contained in the circles of cross-sections of each image is the same). Thus, horizontal cross-sections of each image are circles such that the cross-sections are statistically equivalent in average grey level, spatial frequency, edgeness per unit area, shape of structural elements, and co-occurrence probabilities. It is not hard to see that a 3D classifier based on spatial frequency, edgeness per unit volume, shape of structural elements, or co-occurrence probabilities would show different statistics for each texture.

It is clear that these examples are highly contrived and unlikely to occur in most applications. A more realistic analysis would investigate the texture types indistinguishable by one method (e.g., spatial frequency measurement) but not another (e.g., generalized feature co-occurrence). This is precisely the present

situation being studied in 2D texture classification; a survey of the literature [1] shows that each 2D classification technique achieves high accuracy only for limited classes of image texture.

In summary, we find that the intrinsic ability of a 3D texture classifier to outperform a 2D texture classifier is limited; only in extreme cases will a 3D technique succeed when all 2D approaches fail. Since the variety of 2D texture classification techniques allow high classification accuracy for many types of image texture, the additional information used by a 3D texture classifier is unlikely to make a substantial improvement. Because of the large amounts of data used in texture classification and the additional degree(s) of freedom in the measurments, 3D texture classification is computationally expensive. Thus, its use would not be recommended except in (the unlikely) cases where the textures to be discriminated are difficult to distinguish on the basis of their cross-sections.

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